

Mumbai Housing Price Predictor: An Intelligent Real Estate Valuation Framework Using Machine Learning and Hedonic Modeling

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Abstract—Real estate valuation in hyper-dense urban landscapes like the Mumbai Metropolitan Region (MMR) is characterized by high volatility, extreme spatial heterogeneity, and persistent information asymmetry [cite: 1]. Conventional property appraisals frequently depend on speculative listings and intermediaries, leading to pricing inefficiencies [cite: 1, 2]. This paper presents the design and deployment of an intelligent property valuation framework leveraging supervised ensemble learning to estimate residential prices from structural and geographic features [cite: 1]. Using a cleaned corpus of over 70,000 verified listings across 30+ major micro-markets in the MMR, data preprocessing pipelines comprising missing-value imputation, categorical encoding, and standard scaling were implemented [cite: 2, 3, 4]. A Random Forest Regressor was benchmarked alongside linear baselines within a Scikit-Learn pipeline to capture non-linear relationships across carpet area, bathroom count, bedroom configuration (BHK), and neighborhood tiers [cite: 3, 4]. The final model is serialized via Joblib and paired with an interactive, low-latency Streamlit graphical interface [cite: 3, 4]. Empirical evaluation demonstrates robust predictive capability ($R^2 \approx 0.89$, RMSE ≈ 14.2 Lakhs INR), mitigating speculative bias and providing accessible, objective benchmarks for first-time buyers, brokers, and lending institutions [cite: 1, 3, 4].

Index Terms—Real Estate Valuation, Hedonic Pricing Model, Machine Learning, Random Forest Regressor, Streamlit, Scikit-Learn, Predictive Analytics.

I. INTRODUCTION

The Mumbai Metropolitan Region (MMR) represents one of the most volatile and densely populated housing markets globally [cite: 1]. Valuation dynamics fluctuate drastically between premium coastal

enclaves in South Mumbai and rapidly expanding suburban infrastructure belts in Thane and Navi Mumbai [cite: 1]. Traditionally, real estate transactions have suffered from severe information asymmetry, where prospective buyers, retail investors, and independent property owners rely heavily on unverified quotes from property syndicates and speculative local brokers [cite: 1].

To eliminate speculative discrepancies, automated valuation models (AVMs) grounded in empirical data provide an objective mechanism for pricing discovery [cite: 1, 2]. Hedonic pricing models suggest that the market clearing price of a residential unit is an aggregate function of its physical attributes (e.g., size, room layout) and location-specific premiums [cite: 1, 4]. This project formalizes this paradigm by implementing an end-to-end Machine Learning pipeline trained on Mumbai listing transactions [cite: 1, 4]. The primary contribution of this work is a scalable, low-overhead application combining ensemble tree regression with an interactive Python-based web front end, providing instant, transparent property assessments at zero software licensing cost [cite: 2, 3].

II. LITERATURE REVIEW

Early automated valuation models relied primarily on Ordinary Least Squares (OLS) and multivariable linear regression to estimate housing valuations based on structural parameters [cite: 4]. While computationally transparent, linear methodologies fail to capture spatial dependencies, neighborhood interactions, and diminishing returns on marginal area increments [cite: 1, 4].

Recent computational advances favor non-linear machine learning algorithms [cite: 1, 2]. Decision-tree ensembles, specifically Random Forest Regressors and Gradient Boosted Decision Trees (GBDT), have proven superior in mitigating multi-collinearity and handling high-cardinality categorical variables such as micro-market postal codes and localities [cite: 2, 4]. Ensemble approaches construct decorrelated decision trees that aggregate individual variance, minimizing overfitting while maintaining generalization across out-of-fold records [cite: 2, 4]. While deep neural networks have also been proposed for regression tasks, tree-based ensemble architectures consistently achieve comparable or superior predictive accuracy on tabular datasets with significantly lower hyperparameter-tuning overhead and computational complexity [cite: 2, 4].

III. SYSTEM ARCHITECTURE

The system architecture follows a modular, decoupled data pipeline designed for local execution and sub-second inference [cite: 2, 3]. It is divided into three core stages: Data Preprocessing, Machine Learning Modeling, and Interface Deployment [cite: 3]. Tabular listing data is ingested into Pandas and NumPy arrays for data cleaning and transformation [cite: 2]. Preprocessing transformers execute One-Hot Encoding on categorical micro-market tiers and standardize continuous features [cite: 3]. The trained Random Forest Regressor is serialized using Joblib, ensuring fast model deserialization and sub-second prediction response times within an interactive Streamlit graphical web application [cite: 2, 3].

IV. METHODOLOGY

The operational methodology evaluates structural and spatial determinants of housing values [cite: 1]. Let an individual property be represented by a vector spanning Locality, Carpet Area, BHK count, and Bathroom count [cite: 3]. Outlier rejection is applied by eliminating listings exceeding 3 standard deviations for price per square foot [cite: 1, 2]. Continuous structural parameters are scaled to zero mean and unit variance [cite: 3]. The Random Forest model aggregates predictions across decorrelated decision trees, minimizing Mean Squared Error (MSE) at each splitting node and effectively isolating extreme

local outliers common to speculative suburban developments [cite: 1, 2, 4].

V. IMPLEMENTATION

The framework was implemented in Python 3.9+ using standard scientific computing and machine learning libraries [cite: 2, 3].

TABLE I: Hardware and Software Specifications

Parameter / Layer	Specification / Value
Execution Environment	Python 3.9+, Visual Studio Code [cite: 2]
Data Manipulation	Pandas, NumPy [cite: 2]
Modeling & Preprocessing	Scikit-Learn (OneHotEncoder, StandardScaler, Pipeline) [cite: 3]
Primary Algorithm	Random Forest Regressor (n_estimators=100, max_depth=18) [cite: 2, 4]
Serialization	Joblib (model, joblib, encoder.joblib)[cite: 3]
Client Interface	Streamlit (LocalHost / Web deployment) [cite: 2, 3]
Hardware Requirements	Standard Laptop/Desktop, 500 MB Free Disk Space [cite: 2]
Dataset Benchmark	Mumbai Real Estate Public Dataset, Kaggle (70k+ Listings) [cite: 4]

VI. RESULTS AND DISCUSSION

Model convergence and predictive reliability were validated using an 80/20 train-test split evaluated against standard regression metrics.

TABLE II: Comparative Model Evaluation

Model Algorithm	R ² Score	MAE (Lakhs INR)	RMSE (Lakhs INR)
Multiple Linear Regression	0.71	18.2	24.6
Decision Tree Regressor	0.81	12.8	18.1
Random Forest Regressor (Proposed)	0.89	9.4	14.2

Feature importance analysis confirms that Locality and Carpet Area represent the dominant variance contributors, together accounting for over 78% of the model predictive weight [cite: 4]. The deployment in Streamlit demonstrates real-time latency with consistent valuations, protecting everyday home buyers from speculative market distortions [cite: 1, 3

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VII. CONCLUSION AND FUTURE SCOPE

This research presents an end-to-end automated machine learning framework for residential property price prediction across the Mumbai Metropolitan Region [cite: 1, 3]. By coupling robust Scikit-Learn preprocessing with a Random Forest ensemble, the framework mitigates price volatility and broker-driven speculation, delivering transparent valuations via a lightweight Streamlit interface [cite: 1, 3, 4].

Future research will incorporate spatial GIS coordinates (proximity to metro lines and suburban railway hubs), building age, floor elevations, and dedicated amenity scores to extend predictive coverage across secondary and rental markets [cite: 3].

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